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ABSTRACT

The performance of the University of Arizona College of Medicine's graduating class of 1976 on the National Board of Medical Examiners (NBME) Parts I and II was analyzed in a structural equation model. Although the primary emphasis of this paper is toward model development, the effects of several background and demographic variables such as age, sex, socioeconomic and marital status were estimated, together with those of several major events in these students' medical school careers. About half of the variance in NMBE I total score could be explained with knowledge of overall undergraduate Grade Point Average (GPA), Medical College Admissions Tests (MCAT) scores, and the students' sex. Over 85% of the variance in NMBE II total score could be explained using the variables shown in the structural equation model. NMBE I performance did not greatly affect NMBE II performance when other variables were included. The methodological techniques used to isolate the effects of these variables can be applied to many other analyses in health professions education. (Author/CTM)

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Technical REPORT

Office of Medical Education

A Mathematical Model to Examine Background Variables and Events which Predict Performance on NBME Tests

James C. Wysocki

18th technical report prepared by the Office of Medical Education. August 1977

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A Mathematical Model to Examine Background Variables and Events which Predict Performance on NBME Tests

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Office of Medical Education

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University of Arizona

This is the 18th in a series of technical reports prepared by the Office of Medical Education. August 1977.

Abstract

The academic performance of medical students on NBME I and II was analyzed in a structural equation model. Although the primary emphasis of this paper is model development, the effects of several background and demographic variables were estimated, together with those of major events in these students' medical school careers.

About half of the variance in NBME I total score could be explained by undergraduate GPA, MCAT scores and the students' sex. Other variables explained about 85% of the variance in NBME II total score. NBME I performance did not greatly affect NBME II performance when other variables were included.

A Mathematical Model to Examine
Background Variables and Events
Which Predict Performance on NBME Tests

There is a common concern among educators in medicine that their evaluation measures may be inadequate. Leaving aside the question of student performance after graduation, health professions educators often worry about the reliability and validity of the tests used to evaluate student performance while in school.

This paper will attempt to show a method of evaluating systems of variables. It will examine various student performance measures and background variables to ascertain their influence on one another. This examination will be done within the context of a pass/fail curriculum, to demonstrate the robustness of this approach with this problem. The approach involves the analysis of the data via path analysis and structural equations models. Both of these methods are interrelated offshoots of linear regression and correlation.

This study was begun on two common sense assumptions. The first was that certain background variables would partially determine a student's performance in medical school (Haley, et al., 1971). The second was that the student's performance would also be affected by any significant events which occured during the course of study in medical school. Examples of background variables include socio-economic status, marital status, age at time of admission, under-graduate performance in terms of grade point average (GPA), aptitude for studies in medicine (as measured by Medical College Admissions Test (MCAT) scores), sex, and so forth. Examples of significant events which occur during medical school include academic problems (e.g., failing a course), health problems (e.g., being unable to attend school because of illness), unusual academic opportunities (e.g., taking a preceptorship or receiving additional training, which nontheless delays one's graduation), and traumatic personal events.

Since no preference is given to candidates on the basis of social class, it is expected that socioeconomic status will have no relationship to medical school performance, i.e., that its influence will be randomly dispersed and thus ineffectual. Indeed, previous research (Fredericks and Mundy, 1967) using Hollingshead's 2 factor index of social class on first year medical students revealed no difference in academic performance by social class. Our expectations conform to this empirical finding (although the reader should be cautioned that this finding has not been replicated by all such studies (Woods, et al., 1967)). On the other hand, other background variables should

significantly influence academic performance. Each variable will be described below. The relationships among them are illustrated in figure 1 and will be discussed later.

Method

Subjects. The University of Arizona, College of Medicine's Office of Medical Education maintains a data bank containing selected information on our medical students. At the time of this writing, the most recent graduating class was chosen for analysis. This class was composed of all those graduating in the calendar year 1976 (N=73). People were included in this class if they graduated in 1976, regardless of their class of origin. The University of Arizona then had a three year curriculum, with students able to extend their time in medical school to more than three years. Those who did so for extended periods of time became part of a later graduating class. Consequently, those entering in 1973 who extended to classes later than the class of 1976 were dropped from this analysis, while those who later became part of the class of 1976 were included. The graduating class of 1976 was thus composed of those making unimpeded progress toward their degree, plus those who extended into that class. Students extending relatively early in their career (during the 14-month Basic Sciences Phase I of the curriculum) are distinguished from those who extend later in their career (during the clerkships and elective phases of the curriculum: Phases II and III).

The class of 1976 tended to be white, middle class, male, unmarried and around 23 years of age at the time of their matriculation (see table 1 below).

Measurement of the variables. Student performance was measured at specific points in time. Background and demographic variables, along with MCAT subscores, GPA and the like, were measured at admission but prior to the start of classes. Extending students are flagged by dummy variables (see "description of the variables" below).

Procedure. Variables were analyzed using ordinary least squares (OLS) multiple regression techniques. Major life events such as health problems, and major academic events such as academic problems were converted into dummy variables coded with a zero if the event did not occur, and a one if the event did occur. The other variables, overall undergraduate GAP, MCAT scores and NBME scores, were on an interval scale and were left in that form.

Description of the variables. Three demographic variables which could have an effect on academic performance are age, sex, and marital status. Age is measured in years, while sex and marital status are dummy variables. In the case of sex, males were coded one, while females were coded zero. For marital status, married students were coded one, while single students were coded zero. Aptitude for

medical school was measured by MCAT subscores, together with undergraduate GPA. GPA was measured on a 1 to 4 scale; the higher the GPA, the better the student's undergraduate academic performance.

Significant events in the student's academic career were classified into two points in time. Events occuring prior to the end of the Basic Sciences Phase I (about 14 months into the course of study), were coded as dummy variables. Events which influenced a student's career during the Clinical phases were included as a separate set of dummy variables. For each period in time, four dummy variables were possible. These were (a) health problems, (b) academic problems, (c) quality of life concerns, and (d) leave of absence reasons. Health problems and academic problems are self explanatory. Quality of life reasons include all sorts of personal reasons such as insufficient time to adequately prepare for class, marital difficulties, and so forth. Leave of absence reasons were given when a student took advantage of an unusual educational opportunity which extended his or her education to four years. In all cases, students extending from prior classes who graduated with the class of 1976 were coded a "1" on one of these four dummy variables. Their new classmates, who maintained unimpeded progress toward the M.D., were coded "0".

While it was theoretically possible that all eight dummy variables might be used, this did not occur for two reasons. First, some of these cells were empty. Second, linear dependencies among the dummy variables made it impossible to estimate their effects simultaneously in one equation. When estimating the NBME II equation, one dummy variable had to be omitted. Academic performance was measured at two times, at NBME I (near the end of Basic Sciences), and at NBME II (near graduation).

Structural equations and path analysis. Both path analysis and structural equation models stem from the methodolcgy of linear regression. In the fit of the data to a linear equation, structural paramiters are estimated. Typically the researcher is concerned with variances, covariances, regression coefficients, correlation coefficients, and standard errors of these measures.

In path analysis, one is concerned with how the correlations among a set of variables give rise to the observed standardized regression coefficients (betas) among them. Additionally, there is an effort made to estimate the direct, indirect and total effects of one variable on another.

In the estimation of a structural equation model, attention is directed toward the estimation of the unstandardized regression coefficients (b's) or the betas as functions of the variances and covariances of the variables. Attention is also given toward minimizing the standard error of the b or beta.

Since the purpose of this paper is to serve as a brief introduction to the method, our attention will be limited toward the more general aspects of model development.

Results. Descriptive statistics for each of the variables are given in Table I. For each dummy variable, the mean indicates the proportion of the class coded "1" on that variable.

TABLE 1

DESCRIPTIVE STATISTICS

VARIABLE	N	MEAN	STANDARD DEVIATION
Age	73	22.671	3.350
Sex	73	.726	.449
GPA	73	3.476	.345
MCATS	73	566.781	67.646
MCATV	73	567.603	76.631
MCATQ	73	602.123	84.022
MCATG	73	552.397	67.516
SES	73	51.301	29.115
Marital Status	73	.288	.456
PH1 Health	73	.014	.117
PH1 QOL	73	.206	.407
PH1 ACAD	73	.096	.297
PH1 LOA	73	0	0
PH 2 and 3 Health	73	0	0
PH 2 and 3 QOL	73	.055	.229
PH 2 and 3 ACAD	73	.014	.117
PH 2 and 3 LOA	73	.014	.117
NBME I Total	73	472.192	92.523
NBME II Total	73	453.219	141.614

The results showed that age was somewhat related to performance on the MCAT general knowledge subscore (MCATG). However, since MCATG was not related to any subsequent variable, both it and age were eliminated from the model to be presented below. Performance on the MCAT quantative test (MCATQ) were also unrelated to any subsequent variable. This variable was also dropped from the analysis. The relationships among the remaining variables are shown in Figure 1.

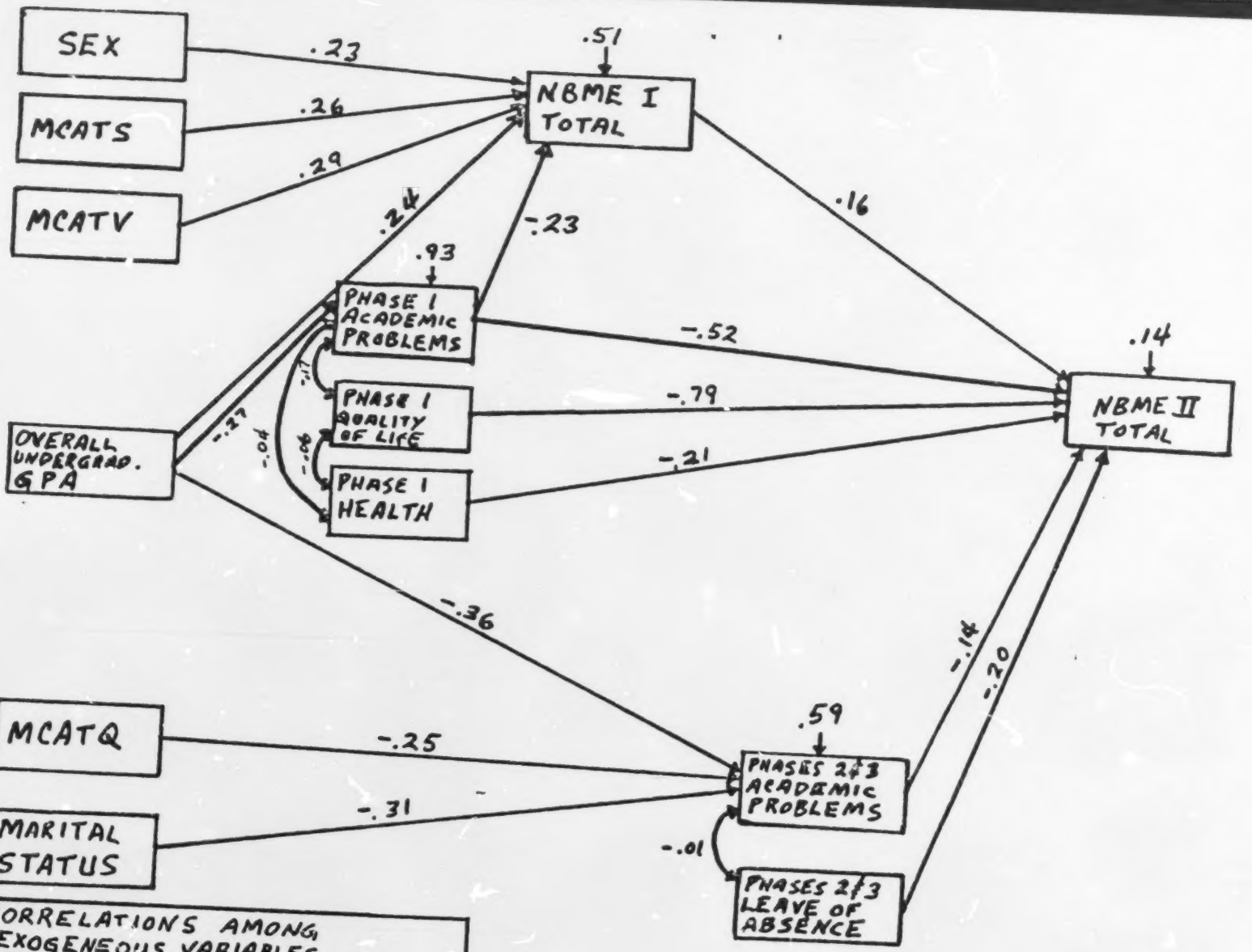

FIGURE 1

CORRELATIONS AMONG EXOGENEOUS VARIABLES

MCATS	.431				
MCATV	.082	.243			
SEX	.329	.204	-.104		
GPA	.268	.186	.109	-.092	
MAR.ST.	-.120	.019	.074	.187	-.170
	MCATQ	MCATS	MCATV	SEX	GPA

PHASE 1 = BASIC SCIENCES PHASE OF THE CURRICULUM
PHASE 2 = CLINICAL " " " " "

This figure shows the structural equation model resulting after non-significant paths were eliminated. Consequently, either the presence or the absence of a path gives the reader useful information. The presence of a path represents an empirically substantiated relationship between two variables. The absence of a path indicates a non-significant path by either empirical or theoretical assertion. Table shows the standardized and unstandardized regression coefficients, standard errors and significance levels for each of the coefficients. Note that in the case of NBME II total score, four dummy variables and one continuous variable (NBME I total score) have been used. Although not shown in table 2, our expectations were borne out in that socioeconomic status, as measured by the Duncan index (Duncan, 1961), was not significantly related to any other variable.

TABLE 2

TESTS OF THE MODEL

INDEPENDENT VARIABLE	BETA	B	STANDARD ERROR OF THE B	SIGNIFICANCE LEVEL, P<
DEPENDENT VARIABLE: PHASE 1 ACADEMIC PROBLEMS				
GPA	-.271	5.631	.098	.020
DEPENDENT VARIABLE: NBME I TOTAL SCORE				
GPA	.240	64.325	26.844	.020
SEX	.229	47.094	20.760	.027
MCAT Quantative	.023	.026	.121	NS
MCAT General	.022	.030	.155	NS
MCAT Science	.263	.359	.144	.016
MCAT Verbal	.289	.348	.139	.015
PH 1 Academic Problem	-.223	-69.576	30.652	.027
PH 1 Health	-.097	-76.899	75.040	NS
PH 1 Quality of Life	.015	3.498	21.483	NS
DEPENDENT VARIABLE: PHASE 2 and 3 ACADEMIC PROBLEMS				
Marital Status	-.312	-.080	-.029	.007
GPA	-.360	-.122	-.035	.001
MCAT Quantative	-.254	-.004	-.002	.030
MCAT S	-.196	-.003	-.002	NS
AGE	.221	.008	.004	NS
SEX	.052	.027	.200	NS
DEPENDENT VARIABLE: NBME II TOTAL SCORE				
Phase 1 Health	-.214	-456.874	101.536	.000
Phase 1 Quality Life	-.790	-485.522	29.859	.000
Phase 1 Academic Prob.	-.515	-434.579	44.705	.000
NBME I Total Score	.158	.428	.149	.006
Phase 2 & 3 Acad.Prob.	-.139	-297.703	104.776	.006
Phase 2 & 3 Leave of Ab.	-.198	-422.668	103.500	.000
Phase 2 & 3 Quality of Li.	-.096	-104.960	52.822	.051(NS)

NS=not statistically significant at .05 level (one tail test)

Correlations among the exogenous variables in Figure 1 are shown in the matrix in the lower right of that figure. Correlations among endogenous variables for which the measured variables exerted no influence are also given in Figure 1. In the case of these endogenous variables, no measured background variable was significantly related to them. The presentation of their correlations in Figure 1 is not common, but perfectly acceptable.

Direct effects of the variables. The direct effects of each of the variables is diagramed in the paths shown on Figure 1. Interpretation of these effects is straightforward. All effects are expressed as standardized regression coefficients, or betas. The remaining numbers indicate residual or unexplained variance, which has a $(1-R^2)$ interpretation. For example, the relationship between overall undergraduate GPA and Phase I academic problems has several ramifications. Since one variable is negatively related to another, an increase in GPA leads to a decrease in the prevalence of academic problems. More specifically, a one standard deviation increase in academic problems leads to a -.27 standard deviation increase in academic problems. However, the residual term of .93 indicates that undergraduate GPA explains only 7% of the variance in academic problems. In practical terms, this means that other variables not measured in this model exert a substantial influence over the prevalence of academic problems. The direct effects of all of the variables can be similarly interpreted.

Indirect effects of the variables. While the exogenous variables (sex through marital status) do not have significant direct effects on NBME II total performance, they do exert indirect effects on it. These indirect effects can be estimated by multiplying through the paths from an exogenous variable through a first level endogenous variable to NBME II total score. For example, undergraduate GPA has several indirect effects. The first is through Phase I academic problems, directly to NBME II; multiplying one path by another gives (-.27) (-.14)=.04. Its second indirect effect is through academic problems and NBME I total score, to NBME II total score; expressed mathmatically, this is (-.27) (-.23) (.16)=.01. A third indirect effect is through Phase II and III academic problems, (-.40) (-.14)=.06. Two more additional indirect effects can be estimated through the common correlation between Phase I academic problems, quality of life, and health reasons. For undergraduate GPA, this is -.27 (path to academic problems) times -.17 (common correlation between academic problems and quality of life), times -.79 (the direct effect quality of life on the NBME II total score), or -.04. In like manner, the last indirect effect can be estimated through the common correlation between Phase I academic problems and Phase I health reasons. This is left as an exercise to the reader, although the small correlation between health and academic problems will lead to almost no indirect effect of undergraduate GPA on NBME II total score by way of this correlation. In like manner all of the remaining indirect effects can be estimated. They are done so along with an example of the computation of the total effect of an exogenous variable in Table 3.

Table 3a
Indirect effects of the variables

Indirect effects of:			
GPA on NBME I total, via Phase I Acad	= (-.27)	(-.23)	= .06
GPA on NBME I total, via Sex	= (.092)	(.23)	= -.02
GPA on NBME I total, via MCATS	= (.186)	(.26)	= .05
GPA on NBME I total, via MCATV	= (.109)	(.29)	= .03
Sex on NBME I total, via GPA	= (-.092)	(.24)	= .02
Sex on NBME I total, via MCATS	= (.204)	(.26)	= .05
Sex on NBME I total, via MCATV	= (-.104)	(.29)	= -.03
MCATS on NBME I total, via Sex	= (.204)	(.23)	= .05
MCATS on NBME I total, via GPA	= (.186)	(.24)	= .04
MCATS on NBME I total, via MCATV	= (.243)	(.29)	= .07
MCATV on NBME I total, via Sex	= (-.104)	(.23)	= .02
MCATV on NBME I total, via GPA	= (.109)	(.24)	= .03
MCATV on NBME I total, via MCATS	= (.243)	(.26)	= .06
Phase I Health or NBME I total, via Ph-l Academic Problem	= (-.04)	(-.23)	= .01
Phase I Quality of Life on NBME I total, via Phase 1 academic problems	= (-.17)	(-.23)	= .04
GPA on Phase II and III Academic problems, via MCATQ	= (.268)	(-.25)	= -.07
GPA on Phase II and III academic problems, via marital status	= (-.170)	(-.31)	= .05
MCATQ on Phase II and III academic problems via marital status	= (-.120)	(-.31)	= .04
MCATQ on Phase II and III academic problems via GPA	= (.268)	(-.36)	= -.10
Marital status on Phase II and III academic problems, via MCATQ	= (-.120)	(-.25)	= .03
Marital status on Phase II and III academic problems, via GPA	= (-.170)	(-.36)	= .06
Phase I academic problems on NBME II total, via NBME I total	= (-.23)	(.16)	= .04
Phase I health on NBME II total, via Phase I quality of life	= (-.06)	(-.79)	= .05
Phase I health on NBME II total, via Phase I academic problems	= (-.04)	(-.52)	= .02
Phase I health on NBME II total, via Phase I academic problems and NBME I total	= (-.04)	(-.23)(-.16)	=.00
Phase I of quality of life on NBME II total, via Phase I health	= (-.06)	(-.21)	= .01
Phase I of quality of life on NBME II total, via academic problem	= (-.17)	(-.52)	= .09
Phase I quality of life on NBME II total, via Phase I academic problem and NBME I total	= (-.17)	(-.23)(.16)	=.01
Sex on NBME II total, via NBME I total	= (.23)	(.16)	= .04
GPA on NBME II total, via NBME I total	= (.24)	(.16)	= .04

Table 3a Continued

Indirect effects of (continued):				
MCATS on NBME II total, via NBME I total	= (.26)	(.16)	=	.04
MCATV on NBME II total, via NBME I total	= (.29)	(.16)	=	.05
GPA on NBME II total, via Phase II and III academic problems	= (-.27)	(-.52)	=	.14
GPA on NBME II total, via Phase II and III academic problem and NBME I total	= (-.27)	(-.23)	(.16)	=.01
MCATQ on NBME II total, via Phase II and III academic problems	= (-.25)	(-.14)	=	.04
Marital status on NBME II total, via Phase II and III academic problems	= (-.31)	(-.14)	=	.04
Phase II and III academic problems on NBME II total, via Phases II and III leave of absences	= (-.01)	(-.20)	=	(-.20)=.00
Phase II and III leave of absence on NBME II total, via Phase II and III academic problems	= (-.01)	(-.14)	=	(-.14)=.00

NOTE: The indirect effects of the exogenous variables (e.g., sex, GPA, etc) on NBME II total score which were due to their correlations with other exogenous variables have been omitted for brevity of presentation.

Table 3b

Computational example: the total effect of sex on NBME I total score

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Exogenous variable=Sex Endogenous variable=NBME I total score

Indirect effects:

Direct effect thru GPA, MCATS, MCATV

Total effect=(.23)+(.02)+(.05)+(.03)+(-.092)(.24)+(.204)(.26)+(-.104)(.29)+(-.092)(-.27)(-.23)

Common correlations: thru GPA, MCATS, MCATV

Indirect path thru correlation with GPA, thru Phase I academic, to NBME I total score

Therefore, total effect of sex on NBME I = (.23) + (.10), or

Total effect = .33

NOTES: 1) Total effect = direct effect + all possible indirect effects.
2) The total effect of any exogeneous variable upon any exogeneous variable can be computed using this example as a guide.

Discussion

If the patterns among the variables are observed over time, it can be seen from the residual variance in Figure 1 that as time goes on, the background variables exert an ever-diminishing effect on academic performance. On the other hand, those variables which indicate certain significant events during medical school exert an ever-increasing influence on NBME test performance. Note the substantial rise in explained variance from NBME I total score to NBME II total score in Figure 1. These results are substantially better than those reported by Carol and Pigman (1966).

Explained variance is, however, only one indicator of the adequacy of a structural equation model. Other tests that a variable must pass to survive in such a model include tests of statistical significance and tests of substantive or theoretical relevance. In Figure 1, all paths not statistically significant were eliminated. If the researcher has a substantive reason for including such paths, he should do so with the understanding that if this path really exists then he has made a mistake elsewhere. For example, assume that y is regressed on X_1, X_2 and X_3, and the theory states that X_1 must influence Y. If that coefficient (b_{yx1}) is not statistically significant then something affecting X_1 X_2 and/or X_3 is not included in that equation. If the hypotheses generated by one's theory is not false, then one must include another variable in this regression equation, or else remove X_2 and/or X_3. Examinations of (1) the standard errors of X_1 through X_3, and (2) the correlations among them gives the researcher clues as to how to proceed.

In other cases, potential exogenous (or causal) variables have no theoretical justification for their inclusion. Some of the potential exogenous variables, such as in-state vs out-of-state undergraduate school, were not included for substantive reasons. Demographic variables such as sex and marital status were included because previous research has demonstrated their relevance to academic performance (Jencks, et al., 1972), while a similar body of research (Haley, et al., 1971; Lanzoni and Kayne, 1976) indicates the relevance of MCAT scores, NBME scores and undergraduate GPA. Health, quality of life, academic problems, and leaves of absence all represent significant events in the life of a medical student. Each of these events alters that student's undergraduate medical career in some significant way. The extent and direction of that significant way was tested in this model. NBME performance was included because of its relationship to academic performance (Woods, et al., 1967), and because of its acceptance in our field. If one wanted to do other research using this methodology, additional measures of student performance can be tailored to fit the researcher's particular needs.

Note that this model also incorporates other relationships which have already been validated in previous research. For example, MCAT science and MCAT verbal scores are each significantly related to performance on NBME Part I. In this respect, the University of Arizona students are like their counterparts in other medical schools (for example, Woods, et al., 1967, provides us with similar results). Since this relationship obtains at other schools besides Arizona, it adds credence to this portion of the model in Figure 1.

Strategies for model development. It is possible to formulate alternative models which fit the data just as adequately as that of Figure 1. Figure 2 illustrates a simple modification to the first model.

Some might assert that background variables influence MCAT performance. If we wish to test this assumption, we can do so by regressing each of the MCAT subscores on them. Figure 2 shows the results of these tests. Paths to MCAT scores which are not significant at the .05 level have been omitted for the sake of clarity of presentation, while all those from MCAT scores to NBME I were retained so that their discussions, below, will be clearer. Additional paths create more indirect effects for the background variables. For example, GPA is then still more influential to ACAD, by way of its path through MCATQ to ACAD.

Methodologically, one can follow certain procedures in the evaluation of a model. Tests of the adequacy of a model are determined by its "goodness of fit" to the data via some variant of the general linear model (Fenessey, 1968). The model is evaluated by means of an F-test or chi-square statistic. However, the choice between alternative models, each of which fits the data about equally well, can only be made with reference to some theory-based criteria. These criteria are unrelated to the methodology of multiple regression; instead they are related to some causal ordering of the variables. In the case of Figure 2, causal ordering is imposed on the variables by the order of events in an applicant's life. The applicant's age and sex are ascribed at birth, while marital status is taken as a given event by the time of admission. Undergraduate GPA is primarily achieved prior to taking the MCAT exams. The order of these events in time consequently give us good reasons for ordering them as shown in Figure 2.

An examination of Figure 2 can also yield a simplified model. As previously mentioned, it was found that age was a significant determinant of performance on the MCATG subtest; MCATG itself was unrelated to any subsequent endogenous variable. In this case, both MCATG and age can be dropped from the model. The result is a more parsimonious model, which can more easily be interpreted.

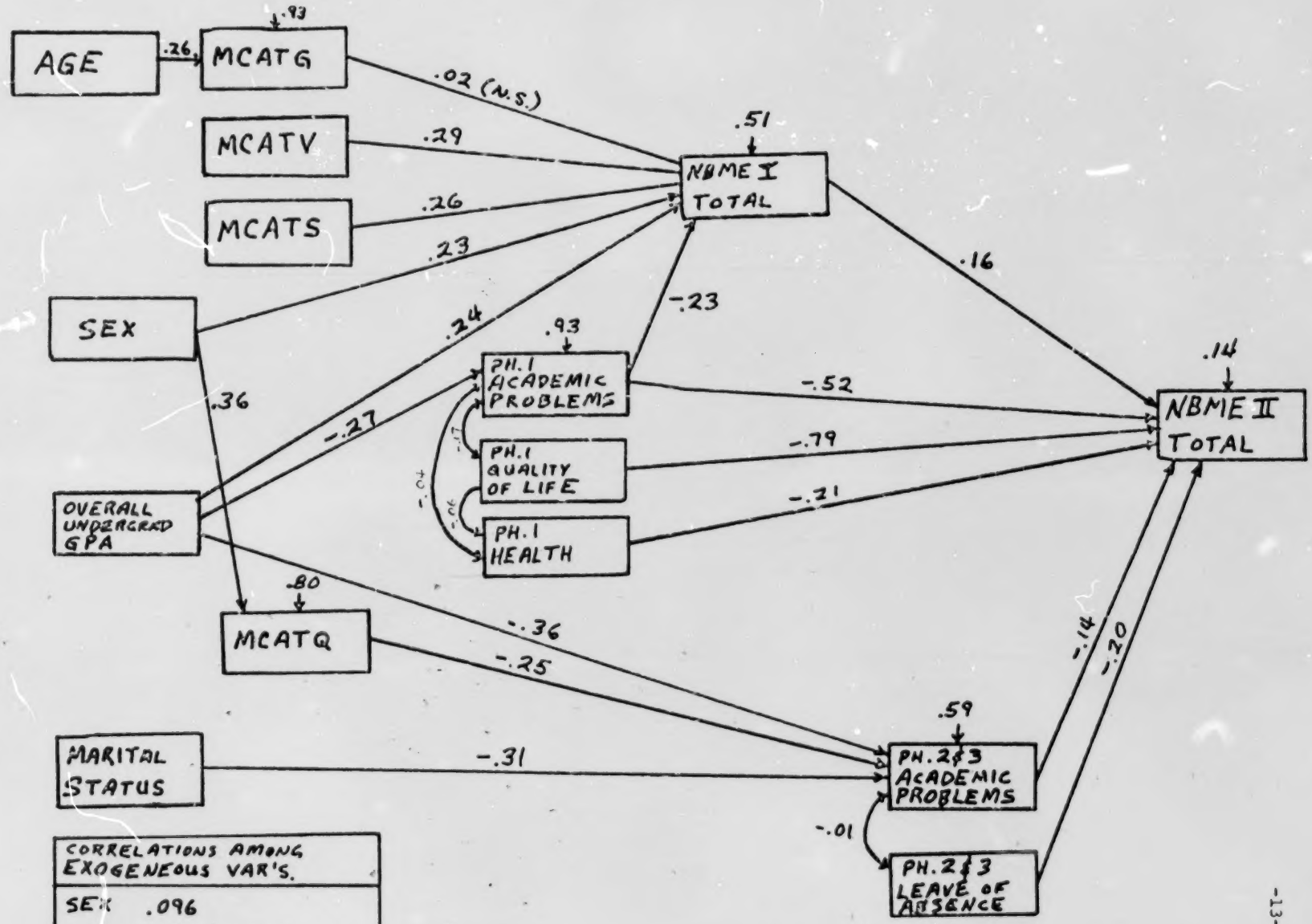
AGE
.26
.93
MCATG
.02 (N.S.)
MCATV
.29
MCATS
.26
.23
SEX
.24
.36
-.27
OVERALL UNDERGRAD GPA
.80
MCATQ
.51
NBME I TOTAL
-.23
.16
.93
PH.1 ACADEMIC PROBLEMS
PH.1 QUALITY OF LIFE
PH.1 HEALTH
-.17
-.04
-.26
-.52
-.79
-.21
.14
NBME II TOTAL
-.36
-.25
MARITAL STATUS
-.31
.59
PH.2&3 ACADEMIC PROBLEMS
-.01
PH.2&3 LEAVE OF ABSENCE
-.14
-.20
CORRELATIONS AMONG EXOGENEOUS VAR'S.
SEX .096
GPA -.248 -.092
MAR. ST. .508 .187 .170
AGE SEX GPA
N.S.= NOT STATISTICALLY SIGNIF.

FIGURE 2

In like manner, socioeconomic status (SES) was dropped, since it did not significantly affect any other variable in either model. Applicants are admitted into medical school on the basis of other criteria than social class. It is therefore not surprising that the effects of this variable, which is so influential to the life of the "man on the street", have been neutralized by those of the admissions criteria.

To see whether age, sex and marital status indirectly influenced medical school performance in other ways, GPA was regressed on them. No significant relationship was found. It is not known exactly when each applicant was married, i.e., exactly how far into or after their undergraduate education began that each married applicant took a spouse. Therefore, marital status could have been causally related to GPA for some students but not for others. For this reason, marital status was not likely to affect GPA for the group as a whole.

It is somewhat surprising that age and sex are unrelated to GPA. But if we remember that GPA is an overall, general measure of performance, we might hypothesize that significant differences in performance by sex in one area such as quantitative skills would be nullified by different performance levels in other areas. GPA may be too general a measure to detect such effects. In other words, its measurement error could conceal the effects of age and sex on specific aspects of academic performance. This is exactly the case. An analysis of the MCAT subscores in Figure 2 reveals differences in performance by sex and age that would be expected when using refined measures.

These models conveniently illustrate the results of refining one's measurement techniques. Indeed, this entire section illustrates some of the methodological manipulations that can be done with this type of model, considering the theoretical underpinnings of the structural equation.

There are two sets of conclusions to be drawn from this model. The first concerns the appropriateness of the model to the problem. The second concerns the predictions of NBME performance. Both conclusions are relative to one another.

One of the unstated assumptions of this model is that human behaviors are patterned, that they fall within defineable limits, and that they can therefore be estimated. The successful estimation of the regularities of medical student academic behavior gives an indication of the validity of the mathematical model used here. If the model had no validity, we would simply have been unable to explain any significant proportion of NBME performance. This is not to say that every equation in the model is accurate. We only assert here that, taken as a set, the structural equation "explain" a great deal of the variance in NBME performance.

Because a great proportion of the explained variance is captured by the structural equations, we can quite accurately predict NBME performance using the variables in these equations. In essence, any interruption of a students medical school curriculum will decrease his performance on NBME II, while a good performance on NBME I will tend to increase his performance on NBME II. Even the opportunity of a special clerkship (measured as a leave of absence) will decrease that students NBME II performance. The high explained variance ($R^2 = .86$) indicates quite accurate prediction by the use of these particular variable. While some of these variables do not occur at other institutions, I feel assured that similar ones can be used by others when examining the performance of their students. Any variable which tap the interpretation of student progress will probably be related significantly to NBME performance.

Summary. The focus of this paper has not been to delve into the intricacies of multiple regression, structural equation models, or the idiosyncrasies of institutional research at a particular state university. It has been instead to illustrate the utility of a particular methodology for research in health education. Structural equation models emphasize the estimation of the parameters (e.g., variances, covariances and regression coefficients), of a mathematical model (Duncan 1975). These models are useful in that they can be used as prediction tools in many situations. Indeed, as more schools require passing grades on NBME tests, the model developed here and its methodology may increase in their utility to other medical school.

A related technique is that of path analysis. Path analysis (Land, 1969) emphasizes the inter-relationships among sets variables on one another. The estimation of direct, indirect, and total effects given in this paper are examples of path analytic techniques. I hope this paper has been useful in its explication of a particular problem solving technique. It has tried to illustrate the interplay between a sketchy underlying theory, expressed as explicitly as possible, and the examination and refinement of that theory through the quantitative tests of a model based on it.